Smart meter roll-out strategy and its effect on energy savings at community level

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Household Energy Use in the UK

- Buildings consume 20%–40% of total energy.
- Energy consumption results from both technological and behavioural causes.
- UK households are due to be fitted with smart meters by 2019.
- Part of this will be the "In Home Display" (IHD) to give occupants feedback on energy use.
- There is potential for such displays to deliver feedback about the occupants' own energy use compared to that of others, for example the average of their local neighbourhood or district.

Strategic Smart-Meter Roll-Out

- One aspect that could make a difference in peer-comparison applications is the order in which smart-meters are installed.
- Evidence suggests that peer feedback results in lower energy consumers increasing their energy consumption towards the average whilst higher energy consumers try to reduce their consumption resulting in a "regression towards the mean" effect. [5]
- Could this be used to design roll-out strategies to ensure a better systemsatic end-result?

Energy Consumption Distributions

The total consumption in each band is given by multiplying usage u (kWh/d) by number of users $F(u)$ in that usage bracket. $G(u) = uF(u)$

The total for all users *up to each band* is the cumulative sum to this value: $T(x) = \sum_{u=0}^{u=x} uF(u)$

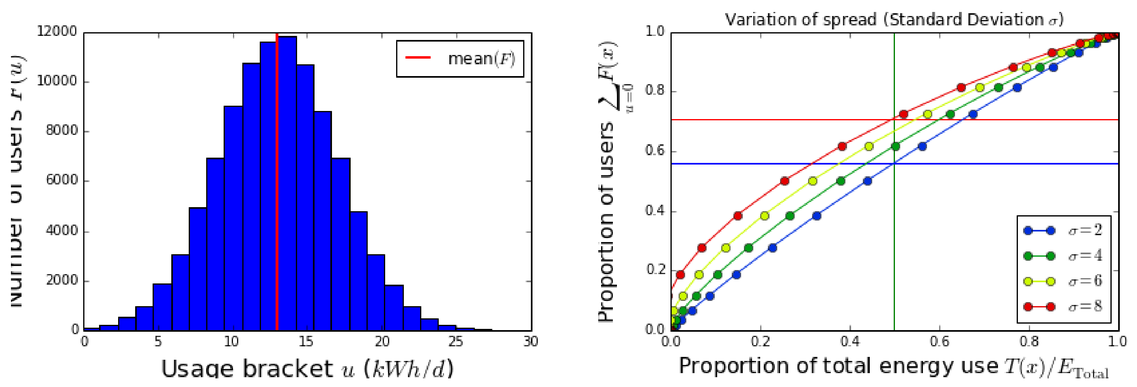

Figure 1: Normally distributed consumption, varying standard deviation σ

- High-end tail contributes disproportionately to energy consumption.
- Wider spread of consumption values makes the effect worse.

Actual Reported Data

Real data is not normally distributed [1]:

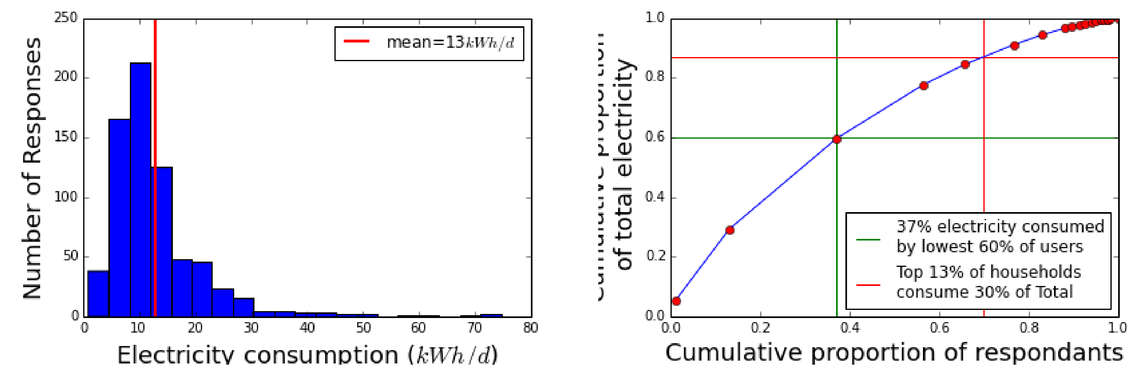

Figure 2: Real data has long-tail

- Effect of high-end tail is exaggerated further.
- Lightest 60% of households consume only 37% of energy but highest 13% use 30% of total.

Model Distribution

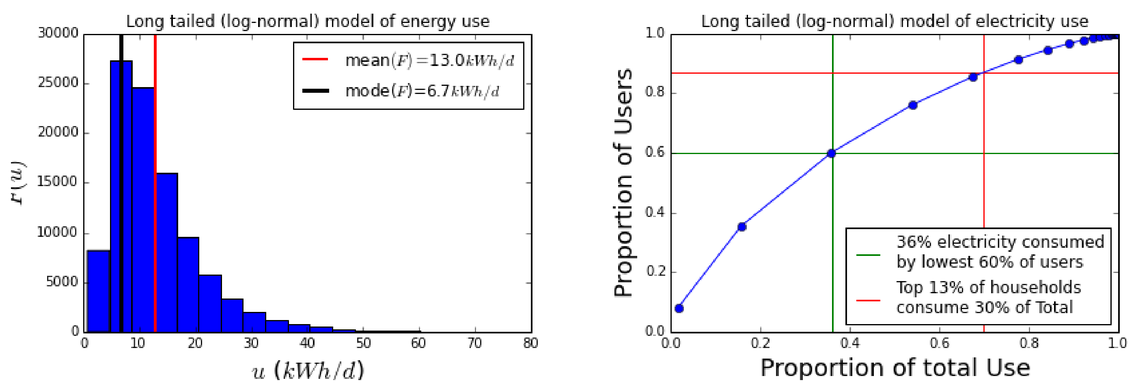

Figure 3: Log-normal distribution used to model the data

- Log-normal distribution can be used to reproduce the features of the real data well.

Energy Behaviour

Adoption of energy-efficient technology/practices are based on a combination of factors [2, 3]:

a) rational choices based on perceived intrinsic benefit;
b) social diffusion of idea influenced by inter-personal communication (*social capital*);
c) interaction with the "mainstream" via observation, media, IHD feedback...

Responding to Different Feedback

- Different types of visual displays can be used.
- feed-back information about own-use as well as peer comparison.

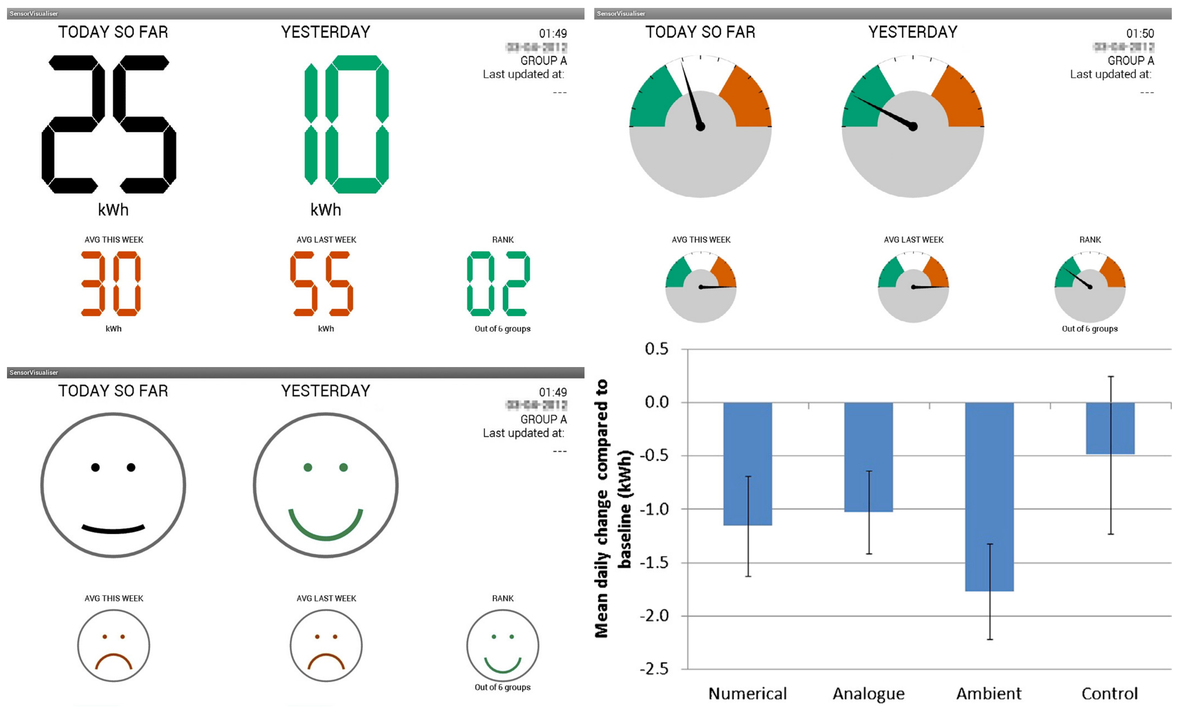

Figure 4: Numerical, analogue and ambient IHD designs and their relative effectiveness. All work well in influencing behaviour [4].

Asymmetry in Behaviour

Studies show that people respond asymmetrically:

1. Higher than average users reduce energy consumption while low-end users increase [5], unless feedback implies good or bad behaviour (such as smiley faces)...
2. Lower-income households have higher incidence of uptake of energy efficiency measures [6],.
3. People respond to social cues differently depending on the importance of the decision [7].

Modelling Asymmetric Responses

Figure 5: Modelling of effect 1. (above) showing the improved average.

Conclusions

- Data shows that higher-than-average users both (a) contribute disproportionately to energy use and (b) respond differently to feedback and intervention campaigns.
- We have analysed models taking these effects into account to look at the best strategies for introducing peer feedback through the smart metering infrastructure.
- The results show that effort must be made to influence the high-end users and that the type of display is important in achieving the best result possible.
- The choice of information (mean average or peak) is important for achieving better results.

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